AUV-Aided Energy-Efficient Data Collection in Underwater Acoustic Sensor Networks

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***Abstract*—With the development of the Internet of Underwater Things (IoUT), two critical problems have been prominent, i.e., the energy constraint of underwater devices and large demand for data collection. In this article, we introduce an autonomous underwater vehicle (AUV)-aided underwater acoustic sensor networks (UWSNs) to solve these problems. To improve the performance of UWSNs, we formulate an optimization problem to maximize the energy consumption utility, which is defined to balance the energy consumption and network throughput. To solve this optimization problem, we decompose it into four parts. First, due to the constraint of communication distance, we construct a cluster-based network and formulate the selection of cluster heads as a maximal clique problem (MCP). Second, the clustering algorithm is proposed. Third, we design a novel media access control (MAC) protocol to coordinate data transmission between AUV and cluster heads, among intracluster nodes, as well as among intercluster nodes. Finally, path planning of AUV is formulated as a traveling salesman problem to minimize AUV travel time. Based on the above analysis, two algorithms, namely, AUV-aided energy-efficient data collection (AEEDCO) and approximate AUV-aided energy-efficient data collection (AEEDCO-A), are developed accordingly. The simulation results show that the proposed algorithms perform well and are very promising in UWSNs with demand for large-scale communication, large system capacity, long-term monitoring, and high data traffic load.**

***Index Terms*—Autonomous underwater vehicle (AUV)-aided underwater acoustic sensor network (UWSN), data collection, energy consumption, energy model, Internet of Underwater Things (IoUT), network throughput.**

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I. Introduction

SINCE marine exploration is in the process of vigorous trend worldwide, the concept of smart oceans has been put forward to monitor the vast marine area. The Internet of Underwater Things (IoUT), defined as a network of smart interconnected underwater objects [1], is regarded as one of the most important technologies in smart oceans. Different from the conventional microwave radio in terrestrial wireless communications, sound waves are regarded as the most suitable paradigm for reliable long-distance communications under the sea because of its less propagation attenuation and longer transmission distance than the electromagnetic waves and light waves. Thus, the underwater acoustic sensor networks (UWSNs) become an indispensable part of IoUT, which play a remarkable role in various fields, such as environmental monitoring, marine science, marine resources development, equipment control and navigation, and military [2]–[4]. In such applications, a large number of sensor nodes equipped with acoustic modems are densely deployed to collect data and send data to the sink nodes that are connected with the data center at land.

However, at the current stage of acoustic modem development, to establish such UWSNs with demand for *large-scale communication, large system capacity, long-term monitoring*, and *high data traffic load*, several obstacles cannot be bypassed. First, the communication distance of acoustic modems [5], [6] is limited. Therefore, to some extent, long-distance communications between acoustic modems are not reliable. Second, it is intractable to charge underwater nodes to ensure enough energy. Finally, the transmission power varies greatly with communication frequency and distance. Hence, how to design an efficient mechanism for UWSNs to collect and transmit data with the limited capability of acoustic modems is an urgent task.

Recently, several works have been proposed to apply multihop routing to transmit data in UWSNs [7]–[11]. Unfortunately, multihop routing schemes suffer from several disadvantages, such as unbalanced energy consumption, unreliable communication connection, and long end-to-end delay [12]. Furthermore, with the prosperous development of autonomous underwater vehicles (AUVs) and unmanned underwater vehicles (UUVs), mobile node-assisted data collection strategies have been shown as an effective way. Since AUVs are embedded with the function of data collection, storage, and computing service, they could play the role of organizing and managing the network to store data and share the burden of computing. In UWSNs, AUV travels around to access anchored sensor nodes and gather data from them, which helps save the transmission energy of sensor nodes due to shorter transmission distance. However, this solution also introduces long collection delays as well as low throughput due to the slow velocity of AUV [13]. Hence, in AUV-aided UWSNs, the main problem is to make a tradeoff between energy consumption and network throughput.

To tackle these challenges, we are motivated to not only plan the path of AUV to reduce its travel time and improve network throughput but also establish the network model prudently to optimize the energy consumption.[1] Thus, this article proposes an AUV-aided energy-efficient data collection (AEEDCO) algorithm. Benefiting from the energy efficient as well as reducing the traveling time of AUV, a cluster-based network is constructed, in which the cluster head nodes play the leading role to collect data from the intracluster nodes and send data to AUV when AUV approaches them. The AUV also plays the role of constructing clusters, selecting cluster heads, and updating its travel path. Therefore, in this article, we investigate the following four issues: 1) the selection of cluster heads; 2) the clustering algorithm; 3) the MAC protocol; and 4) the path planning of AUV. First, in order to generate separate clusters, the cluster heads should not be within the communication range of each other. Given the constraint of communication distance, the cluster heads selection problem can be formulated as a maximal clique problem (MCP) [14]. Second, nodes are all clustered into their nearest cluster head to reduce the transmission power between cluster heads and intracluster nodes. Third, a MAC protocol is specially designed to coordinate media access between the AUV and cluster heads, among the intracluster nodes, as well as among the intercluster nodes. Finally, the travel path of AUV to access each cluster head is planned to minimize the travel length, which can be formulated as a traveling salesman problem (TSP) [15]. Based on the above, we define a tradeoff factor between energy consumption and network throughput, named energy consumption utility to evaluate the performance of this scheme. Therefore, we select the optimal clustering result from all the possible clustering results based on energy consumption utility. Moreover, to prolong the lifetime, sensor nodes take turns to be the cluster head in each data collection round. Finally, since the MCP and TSP are both NP-hard, we also propose an approximate AEEDCO algorithm (AEEDCO-A) to reduce computational complexity.

The main contributions of this article can be summarized as follows.

1) A cluster-based network is proposed to make a tradeoff between network throughput and energy consumption, in which the tasks are mainly partitioned into four parts.
2) The problem that finds the optimal cluster heads in terms of energy consumption utility is established.
3) An approximate algorithm is proposed to reduce the computational complexity.
4) Simulations with various scenarios are carried out and comprehensive analyses are provided to verify the performance of the proposed AEEDCO and AEEDCO-A algorithms.

The remainder of this article is organized as follows. In Section II, we review the existing AUV-aided data collection strategies in UWSNs. We develop the network model and formulate the optimization problem in Section III. In Section IV, the evaluation mechanism is derived for use in the optimization problem. The detailed description of the proposed AEEDCO and AEEDCO-A algorithms is given in Section V. We validate our proposed algorithms through simulation in Section VI. Finally, the concluding remarks are given in Section VII.

II. Related Works

Several sophisticated schemes have been proposed to address the problem of AUV-aided data collection in UWSNs. To the best of our knowledge, these schemes could be mainly divided into three categories according to their network models [16].

A. Distributed Network

In the mechanisms for the distributed network, nodes are distributed individually and AUV needs to access every node. Thus, energy consumption in UWSNs could be balanced and reduced because AUV can move to each node as close as possible. However, due to the low velocity of AUV, its travel time is generally very long, and thus increases collection delay and reduces network throughput. To reduce the collection delay, a spanning tree covering algorithm [17] was proposed to shorten AUV travel distance in the data-gathering stage. Multiple AUVs were also used for large-scale networks. Furthermore, an unsupervised learning technique, i.e., a self-organized map [18], was also proposed to plan the path of AUV which had limited communication range. In this mechanism, to save travel time, AUV would not access every sensor but ignore some sensors due to their lower priority. This technique could also be extended to multivehicle planning. An online reinforcement learning algorithm [19] was also proposed to plan trajectories for multiple AUVs. With the aim of reducing field uncertainty and saving AUV travel time, AUVs paths were determined and updated based on the current positions of all AUVs and the field knowledge. To prolong the network lifetime, the energy-aware path construction (EAPC) [20] mechanism planned the AUV path according to the travel cost and the forwarding load of each node.

B. Grouped Nodes Based on Fixed AUV Path

These schemes are limited by the fixed path of AUV and the network architecture. Thus, most of them are proposed to avoid collisions between the nodes and improve network throughput. However, a fixed AUV path limits the flexibility of network construction greatly. A mobicast routing protocol [21] with user-defined AUV's route was investigated for 3-D UWSNs, aiming to minimize the energy consumption while maximizing the data collection simultaneously. In [22], network protocols among intercluster nodes and among intracluster nodes

[1] Note that since AUV could be charged, we only consider about the energy consumption of sensor nodes, which consists of transmission, receiving, and idle energy.

were designed to minimize the transmission interference with a fixed-AUV path. In [23], according to the network of virtual sectors, four kinds of AUV paths, such as lawnmower path, shortest path, lowest energy cluster first path, and on-the-way lowest energy cluster first path, were planned based on different goals of the network. These schemes could save processing time and reduce energy consumption. In addition, the multi-AUVs moved along a predefined path in [24]. A probability model and an AUV movement model were developed to guarantee the high availability of data collection. Furthermore, two multihop routing protocols were proposed in [25] and [26]. In the AUV-aided energy-efficient routing protocol (AEERP), AUV moved in a predetermined trajectory and collected data from the nearest node. The shortest path tree (SPT) algorithm was used to allocate nodes to a gateway node. In the AUV-aided underwater routing protocol (AURP), multiple AUVs gathered data from predetermined gateway nodes. The routing path was established based on the broadcast information from gateway nodes.

C. AUV-Aided Clustering Network

These schemes divide network nodes into clusters to enable AUV to only collect data from cluster heads, which greatly shortens the travel time of AUV. They could significantly improve network performance if cluster heads are properly selected and clustering algorithms are well designed. In [27], the AUV planned a path that maximized the collected information while minimizing travel time or fuel expenditure. Three issues were mainly considered in this mechanism. First, the probabilistic neighborhoods were defined by the information quality based on the experimental data. Second, the greedy algorithm was proposed to select cover sets and cluster heads, which helped AUV choose the visiting nodes and plan paths. Third, two kinds of MAC protocols, i.e., random access and time-division multiple access (TDMA), were both evaluated in terms of information gain and mission time. In [28], to balance the energy consumption in the network, a distributed data-gathering scheme was proposed. This scheme allowed the AUV to only visit some selected nodes to reduce the overall transmission power. Furthermore, a stratification-based data collection scheme for 3-D UWSNs was proposed in [29]. A forward set-based multihop forwarding algorithm and a neighbor density clustering-based AUV data-gathering algorithm were applied in upper and lower layers, respectively. As a result, the network energy consumption could be reduced and the network lifetime could be prolonged. Moreover, to balance network energy consumption, the data collection protocol based on the mobility model (DCRTM) mechanism was proposed in [30]. This mechanism established a mobility model for mobile elements and clustered nodes by the K-means algorithm. In this article, it was worth mentioning that AUV was devised as an edge node because of its computing, storage, and mobility abilities. To reduce the collection delay in a large-scale network, the prediction-based delay optimization data collection algorithm (PDO-DC) [16] was developed. The PDO-DC algorithm clustered nodes by the neighbor density clustering algorithm and obtained all clusters' data by traversing fewer cluster heads. In this algorithm, the path of AUV was predicted and calculated by applying kernel ridge regression (KRR). Similar methods have also been proposed in vehicle networks [31], [32]. In addition, there are also some papers that modeled multihop cluster networks. Both the bounded relay hop mobile data-gathering (BRH-MDG) algorithm [33] and the cluster-based mobile data-gathering (CMDG) algorithm [34] aimed to make a tradeoff between the energy saving and data-gathering latency. The BRH-MDG algorithm placed cluster heads on the roots of the SPTs to balance between the relay hops for local data aggregation and the tour length of the AUV. In the CMDG algorithm, sensor nodes with a larger number of neighboring nodes in its d-hop range and a shorter delay time would have a higher chance to be selected as cluster heads.

As mentioned above, the aforementioned studies have focused on different goals to be achieved. Different from the existing studies, we define a metric named energy consumption utility to make a tradeoff between energy consumption and network throughput in this article. We model a cluster-based network. The cluster heads are selected based on the energy consumption utility. Other nodes are all clustered into their nearest cluster heads to reduce energy consumption. The MAC protocol is a schedule-based protocol aiming to improve network throughput by reducing handshaking packets and increasing data transmission rounds. The AUV path planning strategy is also proposed to reduce the collection delay.

III. System Model and Problem Formulation

A. Network Model

In this article, we consider a network with N sensors located in $\mathbb{R}^{\dim}$, where $\dim \in \{2, 3\}$, which yields the 2-D and 3-D problems, respectively. An example of the cluster-based 3-D network model is shown in Fig. 1. In this network, the sensor nodes collect data and then transmit data to their cluster heads. To avoid the disadvantage brought by multihop networks, such as unbalanced energy consumption, unreliable communication connection, and long end-to-end delay, intracluster networks are modeled as one-hop networks. An AUV is deployed to visit cluster heads. When AUV accesses the cluster head, data will be forwarded to AUV. After collecting enough data, AUV will return to the sink node and output data into the data center. In this network, two assumptions are made.

1) Sensor nodes in the network are assumed to be stable. The locations could also be globally known by AUV with the help of location algorithms.
2) The communication distances are assumed to be no greater than the limit d_0, which are decided by modem specification.

In this network, the selection of cluster heads, the clustering algorithm, the underwater MAC protocol among intercluster and among intracluster, and the path planning of AUV are all important issues. Thus, we define an evaluation parameter to describe the tradeoff between energy consumption and network throughput. The energy consumption utility β_C in

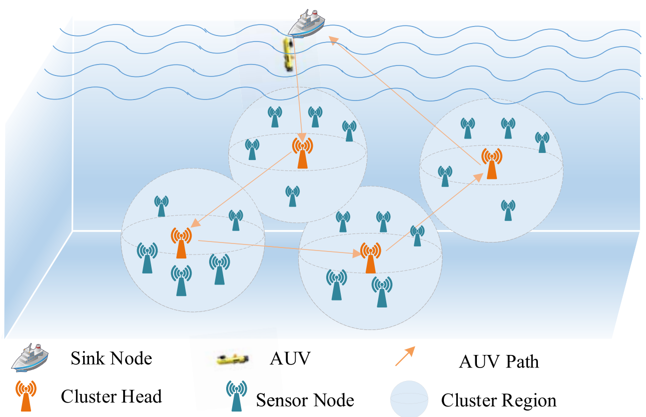

Fig. 1. Example of the 3-D network model.

each clustering is defined as follows:

$$\beta_C = \frac{I_C}{E_C} \tag{1}$$

where C indicates one of the possible clustering result, I_C is the total throughput, and E_C is the total energy consumption in the clustering set. To select the optimal clustering set, in which the value of β_C should be maximal, the following optimization problem can be formulated:

$$\begin{aligned} &\mathrm{Max}_{C\in\mathcal{C}} \quad \beta_C && (2)\\ &\text{Subject to} \quad r_{c_ic_j} > d_0,\ \ c_i, c_j \in C && (3)\\ &\qquad l = \min \sum_{c_i\in C}\sum_{c_j\in C} A_{c_ic_j} r_{c_ic_j} && (4)\\ &\qquad A_{c_ic_j} \in \{0,1\},\ \ c_i, c_j \in C && (5)\\ &\qquad \sum_{c_i\in C, c_i\neq c_j} A_{c_ic_j} = 1,\ \ c_j \in C && (6)\\ &\qquad \sum_{c_j\in C, c_j\neq c_i} A_{c_ic_j} = 1,\ \ c_i \in C. && (7)\end{aligned}$$

In this formulation, the objective function (2) maximizes the energy consumption utility, where $\mathcal{C}$ is the set of all possible cluster heads results. Due to the communication distance limitation, to obtain clustering results covering all nodes, the cluster heads should not be within each other's communication range. Thus, the selection of cluster heads is constrained by (3), where c_i and c_j are the indicator variables denoting the cluster heads in C, and the distance between the selected cluster heads $r_{c_ic_j}$ is larger than the communication range limit d_0. Under the constraint of (3), the set of C could be found by MCP [14]. For this communication network, if we construct a graph G, the vertices are the sensor nodes and the edges are the links between the nodes with distances larger than d_0. A clique is a complete subgraph of G, in which every two vertices are the two endpoints of an edge in G. A maximal clique C is a clique that includes the largest possible number of vertices. In general, there are multiple maximum cliques included in $\mathcal{C}$. Equation (4) is the constraint of AUV path planning to minimize the AUV path length l. Constraints (5)–(7) mean that cluster heads could only be accessed once in one data collection round. A is a matrix denoting link paths between nodes, in which $A_{ij} = 1$ indicating the path goes from i to j, and $A_{ij} = 0$ otherwise. Combining (4) with (5)–(7), it is a classical TSP problem [15], which can be modeled as an undirected weighted graph to minimize the travel path starting and finishing at a vertex (here are the cluster heads) after visiting other vertices exactly once.

B. Channel Model

In underwater acoustic communications, the transmission power (p_{ij}^t) among the nodes i and j varies and could be adjusted based on the characteristic of the underwater channel between nodes, such as signal-to-noise ratio (SNR), frequency (f), and distance (r_{ij}). Assuming that receiving power and idle power are both fixed, the transmission power p_{ij}^t can be expressed as [24], [36]

$$p_{ij}^t = p_0 + \alpha_0 p_{ij} \tag{8}$$

where p_0 is the radio dissipation of running transmitter and receiver circuitry, α_0 is the acoustic and electric conversion efficiency, and p_{ij} is the transmission acoustic power and is denoted by [43]

$$p_{ij} = 10^{((SL_{ij}-170.77)/10)}. \tag{9}$$

Here, SL_{ij} is the source level and defined as

$$SL_{ij} = TL_{ij} + NL_{ij} - DI_{ij} + SNR_{ij} \tag{10}$$

where TL_{ij} is the transmission loss, NL_{ij} is the noise level, the noise for underwater acoustic communications is modeled empirically by noise of turbulence, shipping, and waves in [37] and [38], DI_{ij} is the directivity index and set to 0, SNR_{ij} is the SNR between the nodes i and j, and TL_{ij} is related to transmission distance in meter and frequency in kHz, which can be written as

$$TL_{ij} = k \times 10 \log 10(r_{ij}) + r_{ij} \times 10^{-3}\alpha(f) \tag{11}$$

where k is set to 2 here, corresponding to the cylindrical spreading loss and $\alpha(f)$ is the absorption coefficient which can be expressed empirically by Thorp's formula [43]

$$\alpha(f) = 0.11\frac{f^2}{1+f^2} + 44\frac{f^2}{4100+f^2} + 2.75\times 10^{-4} f^2 + 0.003 \tag{12}$$

where f is the frequency of acoustic waves.

C. MAC Protocol

To monitor the network more efficiently, we propose a MAC protocol to coordinate data packets transmission among intercluster nodes and among intracluster nodes. As mentioned before, AUV plays the role of organizing and managing the network and knows the locations of all nodes, thus it could calculate cluster results based on MCP. In addition, intracluster nodes and AUV are all synchronized in time with the cluster heads. This could be achieved by using the opportunistic information of timestamps attached to packets, such as ACTIVE packets, WAKE packets, DATA packets, and ACK

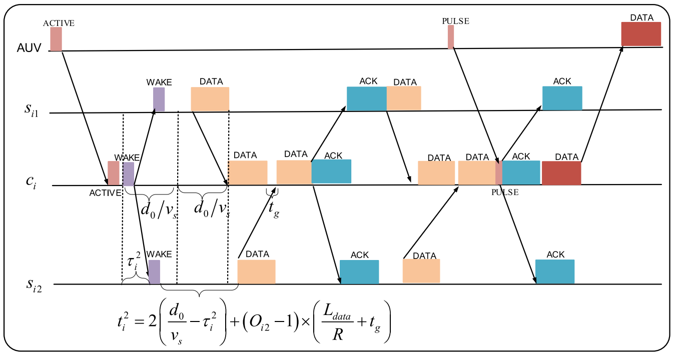

Fig. 2. Example of the MAC protocol in the network.

packets [39]. Accordingly, the clock drift of the time synchronization among cluster heads, AUV, and intracluster nodes can be reduced to 0.15 ms/h for a duration of 4 h, which is acknowledged to be acceptable. Furthermore, to avoid collisions among the intercluster nodes, data packets could only be transmitted when AUV enters the cluster range. Additionally, due to the low velocity of AUV, the travel time from the cluster edge to the cluster head is long enough to allow intracluster nodes to send data in this period. As shown in Fig. 2, four phases are included in the proposed MAC protocol among the intracluster nodes and are explained as follows.

1) *Active Phase:* When AUV enters into a cluster i, it will send an ACTIVE packet to the cluster head c_i. This packet informs the cluster head that data packets transmission could begin in the cluster. The frame of the ACTIVE packet also carries the list of MAC addresses and the sending packets time of the intracluster nodes which could be calculated by AUV. Since AUV knows the distance between intracluster nodes and their cluster heads, it can determine the sending order of intracluster nodes according to the distance. AUV will sort the distance between intracluster nodes and cluster heads in a descending order. The longer the propagation delay is, the earlier the nodes will transmit data packets. Define O_{ij} as the sending order of the intracluster node s_{ij} within the cluster i.
2) *Wake Phase:* When c_i receives the ACTIVE packet, it will broadcast a WAKE packet with maximal transmission power to intracluster nodes and AUV. In addition, c_i also forwards the frame of the ACTIVE packet. Accordingly, when nodes within its communication range receive the WAKE packet, they will know whether they belong to the cluster and what the sending order is. It is worth mentioning that the WAKE packet contains the sending packet time t_{si}.
3) *Data Transmission Phase:* When the intracluster node s_{ij} receives the WAKE packet, they will record their receiving WAKE packet time t_{ri}^j and then calculate the propagation delay as $\tau_i^j = t_{ri}^j - t_{si}$. The nodes will arrange the arriving time of their data packets behind the prior one over the interval of guard time and accordingly calculate the waiting sending time of the data packets. When an intracluster node receives the WAKE packet, it needs to wait for the waiting sending time t_{ij}. As shown in Fig. 2, t_{ij} can be calculated as $t_i^j = 2(d_0/v_s - \tau_i^j) + (O_{ij} - 1)(L_{\text{data}}/R + t_g)$. Then, it will send the data packet as the calculated time. After collecting data packets from all intracluster nodes, c_i will send an ACK packet to them. At the same time, the ACK packet updates and notifies intracluster nodes when to send the packet in the next round. Then, the data transmission cycles in turn until c_i receives the PULSE packet sent by AUV. When AUV moves near the cluster head with the distance of d_r, it will send the PULSE packet to the cluster head. Note that the PULSE packet is short enough so that it would not affect the data transmission among nodes. Thus, the number of data transmission times n_i in the cluster i could be calculated by
$$n_i = \frac{T_{auv} - T_s}{T_i} \tag{13}$$
where T_{auv} is the travel time of AUV in the cluster, which is denoted by AUV travel distance $(d_0 - d_r)$ divided by velocity of AUV (v_{auv}), i.e., $T_{auv} = (d_0 - d_r)/v_{auv}$, T_s is the time of the ACTIVE packet and the WAKE packet, i.e., $T_s = 2d_0/v_s + (L_{\text{active}} + L_{\text{wake}})/R$, and T_i is the data transmission time in one round in the cluster i, containing the propagation time, the ACK packet transmission time, the data packet transmission time, and the guard time, i.e.,
$$T_i = \frac{2d_0}{v_s} + \frac{L_{\text{ack}} + N_i \gamma L_{\text{data}}}{R} + N_i t_g \tag{14}$$
where v_s is the speed of the sound wave under the sea, L_{ack} and L_{data} are the length of the ACK packet and data packet, respectively, γ is the number of data packets transmission once for one node, N_i is the number of nodes in the cluster i, R is the transmission data rate, and t_g is the guard time.
4) *Data Collection Phase:* When c_i receives the PULSE packet, it will wait until the end of the current data packets transmission, and then send the ACK packet to terminate data transmission in the cluster. After that, c_i sends all data packets to AUV.

IV. Evaluation Mechanism

In this section, to evaluate the proposed mechanisms, we need to derive the tradeoff factor energy consumption utility β_C. As mentioned in Section III-A, β_C is related to energy consumption E_C and network throughput I_C. Thus, we will calculate these parameters, respectively.

A. Throughput

Network throughput is defined by the bits of data packet transmission per second and is given by
$$I_C = \frac{L_C}{D_C} = \frac{\sum_{i \in C} n_i \gamma L_{\text{data}} \bar{K}_i (1 - p_e)^{2L_{\text{data}}}}{D_C} \tag{15}$$
where L_C is the total length of data packet received correctly by AUV during one round and consists of data packets from all clusters, p_e is the bit error rate (BER), which is related to

the specification of the modem and the characteristic of the underwater acoustic channel [40]–[42], and $\bar{K}_i$ is the average number of data packets transmission in the cluster i during one round and could be calculated as follows:

$$\bar{K}_i = \sum_{k=1}^{N_i-1} kP^k = \sum_{k=1}^{N_i-1} kC_{N_i}^k P^k (1-P)^{N_i-k} = N_i P \tag{16}$$

where N_i is the number of nodes in the cluster i, and P denotes the probability of generating data packets during one round, which is

$$P = 1 - e^{-\lambda D_C} \tag{17}$$

where λ is the data generating rate in one node, and D_C is the collection delay in one round, consisting of transmission time d_i^t in each cluster, propagation time d_i^p in each cluster, and AUV travel time d_{auv}. In addition, when AUV is traveling, data transmission is also performed in the cluster, so the public time should be subtracted. This is because:

1) when AUV travels from the cluster edge to the cluster head, intercluster nodes transmit data packets with n_i rounds as mentioned in Section III-C. This part of data transmission delay could be ignored since it has been included in AUV travel time d_{auv};
2) when AUV approaches the cluster head and collects data from it, the total delay should include the extra time delay if its travel time is shorter than the data transmission time. However, if not, the data transmission time would be included in AUV travel time.

Thus, the collection delay can be expressed as

$$D_C = d_{auv} + \sum_{i \in C} \max\left(d_i^t + d_i^p - \frac{2d_r}{v_{auv}}, 0\right) \tag{18}$$

where d_i^t could be expressed as the sum of data packet transmission time in this round, as

$$d_i^t = \frac{N_i n_i \left(\gamma L_{\text{data}} + t_g\right)}{R}. \tag{19}$$

Moreover, the propagation delay d_i^p is calculated by

$$d_i^p = \frac{d_r}{v_s}. \tag{20}$$

The AUV travel time d_{auv} can be calculated as the AUV path length l divided by the velocity of AUV v_{auv} when it collects data from all cluster heads. It could be expressed as

$$d_{auv} = \frac{l}{v_{auv}}. \tag{21}$$

From the above analysis, AUV travel time is one of the key factors in the collection delay. Thus, to save time, we should plan the shortest data collection route for AUV.

B. Energy Consumption

Energy consumption of the network consists of transmission energy, receiving energy, and idle energy of all nodes. Transmission power is closely related to the transmission frequency and the distance between the acoustic modems. Hence, we adjust the transmission power on the basis of transmission distance and frequency in the model. Note that receiving power is assumed to be fixed. The energy consumption is defined as

$$E_C = \sum_{i \in C}\left(E_i^t + E_i^r\right) + E_{\text{idle}} \tag{22}$$

where i is the indicator of the cluster and E_i^t is the transmission energy containing the transmission energy of intracluster nodes and cluster heads. Thus, it could be calculated by

$$E_i^t = \sum_{j \in C_i} p_{ij}^t T_{ij}^t = E_{c_i}^t + \sum_{j \in C_i, j \neq c_i} \frac{p_{ij}^t L_{ij}^t}{R} \tag{23}$$

where C_i is the set of nodes in the cluster i, j is the indicator of the intracluster node, p_{ij}^t is the transmission power of the node j and could be calculated through (8), T_{ij}^t is the transmission time for the node j in the cluster i, and L_{ij}^t is the packet length for the node j in the cluster i, which consists of the length of data packets, i.e., $L_{ij}^t = n_i \gamma L_{\text{data}}$. Transmission energy of the cluster head $E_{c_i}^t$ contains the transmission energy of the WAKE packet, ACK packet, and data packets from cluster heads to AUV. It is denoted by

$$E_{c_i}^t = p_{\max}(L_{\text{wake}} + n_i L_{\text{ack}}) + \frac{p_{iauv} N_i n_i \gamma L_{\text{data}}}{R} \tag{24}$$

where $p_{\max}$ is the transmission power of the cluster head and can be given by (8) when the distance meets the communication distance limitation d_0, and p_{iauv} is the transmission power between the cluster head and AUV and it could be calculated by (8) when the distance is set to be d_r.

E_i^r is the receiving energy containing the receiving energy of intracluster nodes and cluster heads. The receiving energy of intracluster nodes mainly consists of that of the WAKE packet and ACK packet, while the receiving energy of cluster heads includes that of the data packet and the ACTIVE packet. Thus, E_i^r could be calculated by

$$E_i^r = \sum_{j \in C_i} p^r T_{ij}^r = \frac{p^r L_{c_i}^r}{R} + \sum_{j \in C_i, j \neq c_i} \frac{p^{r L_{ij}^r}}{R} \tag{25}$$

where p^r is the receiving power, and L_{ij}^r and $L_{c_i}^r$ are the receiving packet lengths between each intracluster node and cluster head in the cluster C_i, respectively. They could be given by

$$L_{ij}^r = L_{\text{wake}} + n_i L_{\text{ack}} \tag{26}$$

$$L_{c_i}^r = N_i n_i \gamma L_{\text{data}} + L_{\text{active}}. \tag{27}$$

E_{idle} is the energy consumption when nodes do not send and receive packets. Thus, we have

$$E_{\text{idle}} = p_{\text{idle}}\left(D - \frac{L_{c_i}^r + L_{c_i}^t}{R}\right) + \sum_{j \in C_i, j \neq c_i} p_{\text{idle}}\left(D - \frac{L_{ij}^t + L_{ij}^r}{R}\right) \tag{28}$$

where $L_{c_i}^t$ is the length of transmission packets for the cluster head c_i, i.e., $L_{c_i}^t = L_{\text{wake}} + n_i L_{\text{ack}} + N_i n_i \gamma L_{\text{data}}$.

As a result, β_C could be calculated. It is also found out that β_C is closely related to the number of nodes in the

TABLE I
NOTATIONS

Name	Description
β_C	Energy consumption utility
E_C	Total energy consumption in one round
I_C	Total throughput in one round
E_i^{t}	Total transmission energy consumption in one round
E_i^{r}	Total receive energy consumption in one round
$E_{c_i}^{\mathrm{t}}$	Transmission energy consumption of the cluster head
p_{ij}^{t}	Transmission energy consumption for one node in one round
p_{iauv}	Transmission energy power between cluster head and AUV
p_{idle}	Idle energy power
p^{r}	Receiving energy power
p_0	Radio dissipation of running circuitry
α_0	Acoustic and electric conversion efficiency
T_{ij}^{t}	Transmission time for one node in one round
l	AUV path length in one round
L_{ij}^{t}	Transmission packets for one node in one round
L_{ij}^{r}	Receiving packets for one node in one round
L_{data}	Length of data packets
L_{wake}	Length of WAKE packets
L_{ack}	Length of ACK packets
L_{active}	Length of ACITIVE packets
v_{auv}	Velocity of AUV
v_s	Speed of sound wave
n_i	Number of data transmission times in cluster i in one round
N_i	Number of nodes in one cluster
R	Transmission data rate
d_0	Maximal Communication range
d_r	The range that AUV begin to collect data from cluster heads

network N, data packet length L_{data}, AUV velocity v_{auv}, and modem settings, such as f, R, d_0, p_{idle}, p^r, p_0, α_0, and *SNR*. The above-mentioned parameters are listed in Table I.

V. Overview of AEEDCO and AEEDCO-A

In this section, we will propose the AEEDCO and AEEDCO-A algorithms in detail to solve the optimization problem (2)–(7), i.e., maximizing the energy consumption utility β_C. Knowing that the optimization problem is NP-hard, we solve this problem by decomposing into four steps: 1) finding cluster heads; 2) constructing the cluster; 3) planning the path of AUV; and 4) rotation of clustering result. The AEEDCO algorithm calculates all β_C of possible clustering results and selects the final clustering results with the maximal energy consumption utility. However, the computational complexity would be very high. To further reduce the computational complexity, we devise another AEEDCO-A algorithm which greedily chooses the cluster heads based on their density and achieves suboptimal results.

A. AEEDCO

The AEEDCO algorithm takes four steps to solve the problem and the details are proposed as follows.

1) *Finding Cluster Heads:* Since the locations of all nodes could be obtained and the communication distance is limited within d_0, the cluster heads should be at least away from each other larger than d_0, which means one cluster head is not in the communication range of the others. Hence, the problem of obtaining the set of cluster heads can be formulated as an MCP. A search algorithm for recursive backtracking, namely, the improved Bron–Kerbosch algorithm in [44], is chosen to solve the MCP with a computational complexity of $\mathcal{O}(3^{N/3})$. So far, the set of all possible cluster heads $\mathcal{C}$ will be obtained. Later, we need to select the optimal one from these sets (lines 1–3).
2) *Constructing the Cluster:* Since the energy consumption utility β_C is related to the distance between the nodes, the shorter the distance is, the smaller the β_C. Therefore, we simply cluster one node with its nearest cluster head each time (lines 4–12).
3) *Path Planing of AUV:* To reduce collection delay, the length of the AUV path should be minimized, which is formulated as a TSP problem. Here, the ant colony algorithm is applied to solve the TSP problem with a computational complexity of $\mathcal{O}(N^3)$. Note that the computation time would be less since the number of cluster heads is generally much less than that of the nodes in the network (line 13).
4) *Selection of Clustering Result:* When all of the clusters have been formed and the AUV path has been planned, we could calculate β_C for $C \in \mathcal{C}$. Then, we sort all β_C and the minimal one is selected as the optimal cluster result (lines 14–16).
5) *Rotation of Clustering Result:* Additionally, to prolong the lifetime of this network, the sensor nodes should take turns to be cluster heads to prevent energy from being drained early. Thus, we follow the ranking of β_C and select the cluster heads to form the cluster in turn. It is worth mentioning that a node might be possibly selected as a cluster head again. Although efforts have been made to avoid this case, we find that it incurs more complexity to rule out the cluster heads selected in the previous round while there is little bonus to the balance of energy consumption of the nodes. Thus, we only choose the cluster heads following the ranking of β_C, not rule out the repeated ones (line 17).

The detailed procedures of the AEEDCO algorithm are shown in Algorithm 1. Fig. 3 is an example of cluster formation and AUV path planning in a 2-D network. Triangular nodes and circular nodes are the cluster heads and sensor nodes, respectively. Different colors represent different clusters while the red circles are the communication range of the cluster heads. The blue line indicates the AUV path.

The runtime is an important performance for optimization algorithms. The computational complexity consists of the computation of the Bron–Kerbosch algorithm, the ergodic searching of all clustering results, and solving the TSP problem. Note that the number of clustering results $\mathcal{C}$ is related to the communication limitation d_0, the number of nodes N, and the scale of the network. Assuming we have M clusters in the network, then, in the worst case, the number of all possible clustering results is C_N^M. Thus, the computational complexity is described by $\max(\mathcal{O}(3^{N/3}), O(M^3 C_N^M))$. Normally, the number of clusters would be much less than the number of nodes, say 6 in the

Algorithm 1 AEEDCO

// Note: r_{ij} is the distance between node i and node j, $i, j \in N$
// Note: To calculate all of the cluster heads by MCP
$\mathcal{C}$=MCP_Bron-Kerbosch(r)
for $C \in \mathcal{C}$ **do**
  $c_i = C(i)$ // Note: cluster heads
  $N_i = N_i+1$ // Note: the number of nodes in each cluster
  for $j \in N$ **do**
    // Note: To clustering all nodes
    $temp = r(j, C)$
    $[r_{min}, i] = \min(temp)$
    put j into C_i; $r_{jc_i} = r_{min}$; $N_i = N_i + 1$
  end for
  L_C=TSP(C)
  calculate β_C
end for
C= sort(β_C)
Then the clustering result will be selected according to the order of the sorted β_C.

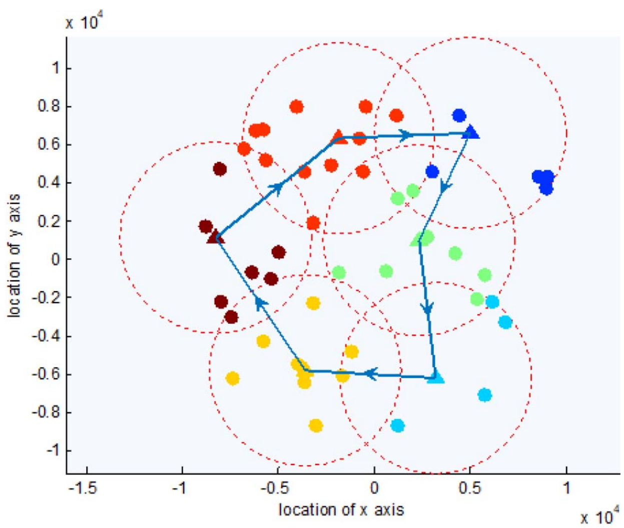

Fig. 3. Example of cluster formation and AUV path planning in the 2-D network.

example of a network with 50 nodes in Fig. 3. In this case, the computational complexity could be $\max(\mathcal{O}(3^{50/3}), O(6^3 C_{50}^6))$, i.e., $O(6^3 C_{50}^6)$.

B. AEEDCO-A

To further reduce computational complexity, we implement a low-complexity algorithm named the AEEDCO-A algorithm, shown in Algorithm 2. When the number of possible clusters gets larger, one can choose the AEEDCO-A algorithm or the AEEDCO algorithm considering the tradeoff between required computation time and network performance. This algorithm applies the greedy method to find the near-optimal solution, different from the AEEDCO algorithm which figures out all the possible cluster heads. We first calculate the density of all nodes ρ, which is defined as the number of nodes within

Algorithm 2 AEEDCO-A

1: // Note: r_{ij} is the distance between node i and node j, $i, j \in N$
2: **for** $i \in N$ **do**
3:   **for** $j \in N$ **do**
4:     **if** $r_{ij} < d_0$ **then**
5:       $\rho(i) = \rho(i) + 1$
6:     **end if**
7:   **end for**
8: **end for**
9: $[\rho_{sorted}, \rho_{ord}]$=sort($\rho$)
10: **for** $n = 1 : N$ **do**
11:   $c_1 = \rho_{ord}(n)$
12:   put $\rho_{ord}(n)$ into C_1
13:   $N_1 = N_1 + 1$
14:   // Note: find all the cluster heads
15:   **for** $i \in \rho_{sorted}$ **do**
16:     **if** $temp = r_{ij} > d_0$ **then**
17:       $N_C = N_C + 1$; // # of cluster
18:       $c_{N_C} = \rho_{ord}(i)$;
19:       put $\rho_{ord}(i)$ into C_{N_C}; $N_{N_C} = N_{N_C} + 1$
20:     **end if**
21:   **end for**
22:   //Note: to clustering all the nodes
23:   **for** $j \in N$ **do**
24:     $temp = r(j, C)$
25:     $[r_{min}, i] = \min(temp)$
26:     put j into C_i; $r_{jc_i} = r_{min}$; $N_i = N_i + 1$
27:   **end for**
28:   L_C=TSP(C)
29:   calculate β_C
30: **end for**

the communication range of one node (lines 1–8). After that, density ρ is sorted and the node with the maximal density is selected as the first cluster head (lines 9–12). Then, we greedily find other cluster head nodes which are d_0 larger away from the selected maximal density node, as well as from each other, based on the density ranking. Repeating this step, all cluster heads can be selected (lines 13–21). Both the cluster formation algorithm and the path planning of AUV follow the same procedures as the AEEDCO algorithm (lines 22–29). In addition, cluster head rotation should be performed to avoid the early energy drain of head nodes. Specifically, the selection of first cluster head would take turns based on the density ranking and then the other cluster heads would be changed accordingly (lines 10–30).

The computational complexity of the AEEDCO-A algorithm consists of the computation of nodes' density, the selection of cluster heads, the constructing of the cluster, and solving the TSP problem. Assuming that the number of clusters is M, the computational complexity is described by $\max(\mathcal{O}(N^2), \mathcal{O}(M^3))$. Specifically, the number of clusters is 6 in the example of the network with 50 nodes in Fig. 3. In this case, the computational complexity could be $\max(\mathcal{O}(50^2), O(6^3))$, i.e., $O(50^2)$.

TABLE II
MODEM PARAMETERS

Modem Name	f (kHz)	R (kbit/s)	d_0 (m)	p_{idle} (W)	p^r (W)	p_0 (W)	α_0 (W)	SNR (dB)	p_e
S2CR 12/24	13-24	9.2	6000	0.285	0.8	2.5	2	10	10^{-5}
S2CR 18/34	18-34	13.9	3500	0.285	0.8	2.8	2	10	10^{-5}

TABLE III
SIMULATION PARAMETERS

Parameter	Value
Network Size	$20000m \times 20000m$
Number of nodes (N)	$10 - 60$
Data generating rate (λ)	0.1
Node Initial Energy (E_0)	$50000 \quad J$
AUV Velocity (v_{auv})	$1 - 10 \quad m/s$
Sound wave speed (v_s)	$1500 \quad m/s$
L_{data}	$20 + 1024$
L_{wake}	$12 + 11 \times N$
L_{ack}	$10 + 2 \times N$
L_{active}	$12 + 11 \times N$
Trial times	20

VI. SIMULATION RESULTS AND DISCUSSIONS

A. Simulation Setup

Simulations are carried out to demonstrate the performance of the proposed AEEDCO and AEEDCO-A algorithms using MATLAB. Since the physical layer of underwater acoustic communication networks varies from different acoustic modems, we set these parameters based on the Evologics acoustic modems [45], which are mature commercial products with different specifications. Here, two kinds of modems are selected, i.e., S2CR12/24 and S2CR18/34. The related parameters, frequency f, data rate R, communication range d_0, powers $p_{\text{idle}}, p^r, p_0, \alpha_0$, and SNR, are presented in Table II. In addition, the BER p_e versus SNR is set according to [40]. Here, when SNR is 20, the BER under coded transmission is lower than 10^{-5}, we set as 10^{-5}.

In addition, the settings of the network are introduced as follows and shown in Table III. In this network, N nodes are all randomly deployed in a 20 000 m $\times$ 20 000 m area. The data generating rate λ is set as 0.1 packets/s. The initial energy of the node is set to 5000 J. The velocity of AUV is set between 1 and 10 m/s and the sound wave speed is set as 1500 m/s. The length of packets ($L_{\text{data}}, L_{\text{wake}}, L_{\text{ack}}$, and L_{active}) are all set based on the packet frame structures. At the same time, the average results of 20 trial times are taken as the final results in case of the randomness.

We compare the performance of the AEEDCO and AEEDCOA algorithms with two related and latest algorithms in AUV-aided UWSNs, i.e., DCRTM [30] and PURETSP. The DCRTM algorithm applies a k-means clustering algorithm and a mobility model of AUV to collect data aiming to reduce energy consumption. In PURETSP, AUV needs to move to each node to collect data aiming to shorten collection delay and improve network throughput. The performances of these algorithms are all evaluated in terms of energy consumption utility, network throughput, energy consumption, and collection delay. A better strategy is supposed to result in larger energy consumption utility, higher network throughput, lower energy consumption, and shorter collection delay.

B. Simulation Results

1) Performance With Different Numbers of Nodes: To compare the performance of these algorithms, we set different numbers of nodes varying from 10 to 60. All algorithms are in the same environment. The modem settings are based on the S2CR12/24 modem, v_{auv} is set as 2 m/s, and γ is set as 8. Fig. 4 shows the performances of these algorithms.

The collection delay is calculated in (18) and shown in Fig. 4(a). It displays that as the number of nodes increases, the collection delay of AEEDCO, AEEDCO-A, and DCRTM remain relatively stable while that of PURETSP climbs up. More specifically, the collection delay of AEEDCO is the smallest. The collection delay of AEEDCO-A is larger than that of DCRTM while it is smaller than that of PURETSP. This is because, in PURETSP, AUV needs to move to each node, while in the other three, they only need to move to the cluster head. In addition, since AEEDCO-A does not obtain the optimal cluster heads result compared with AEEDCO, the distance between the cluster heads may be larger. Thus, its collection delay may be larger than that of AEEDCO accordingly. The results also show that the collection delay in one round is about 5 h. Therefore, it is available for sensors to cache their data in their buffer memories during such a long time.

The network throughput defined in (15) is displayed in Fig. 4(b). In general, it shows that the network throughput of AEEDCO, AEEDCO-A, and DCRTM increases greatly with the number of nodes while that of PURETSP increases slightly. More specifically, the network throughput of AEEDCO and AEEDCO-A is larger than that of the other two algorithms. This is because, in AEEDCO and AEEDCO, nodes could send data packets with n_i number of times in one round resulting in high network throughput. Moreover, their collection delay is also shorter, and according to the calculation in (15), the shorter the collection delay is, the larger the network throughput would be.

Fig. 4(c) shows how the number of nodes influences the energy consumption, which is defined as the energy consumption per second, i.e., E/D. The results show that the energy consumption of the four algorithms increases with the number of nodes in general. However, the energy consumption of AEEDCO is higher than the others. This is because the collection delay of AEEDCO is shorter than the rest algorithms. Moreover, since more data packet consumes more energy, the larger the throughput is, the higher the energy consumption would be.

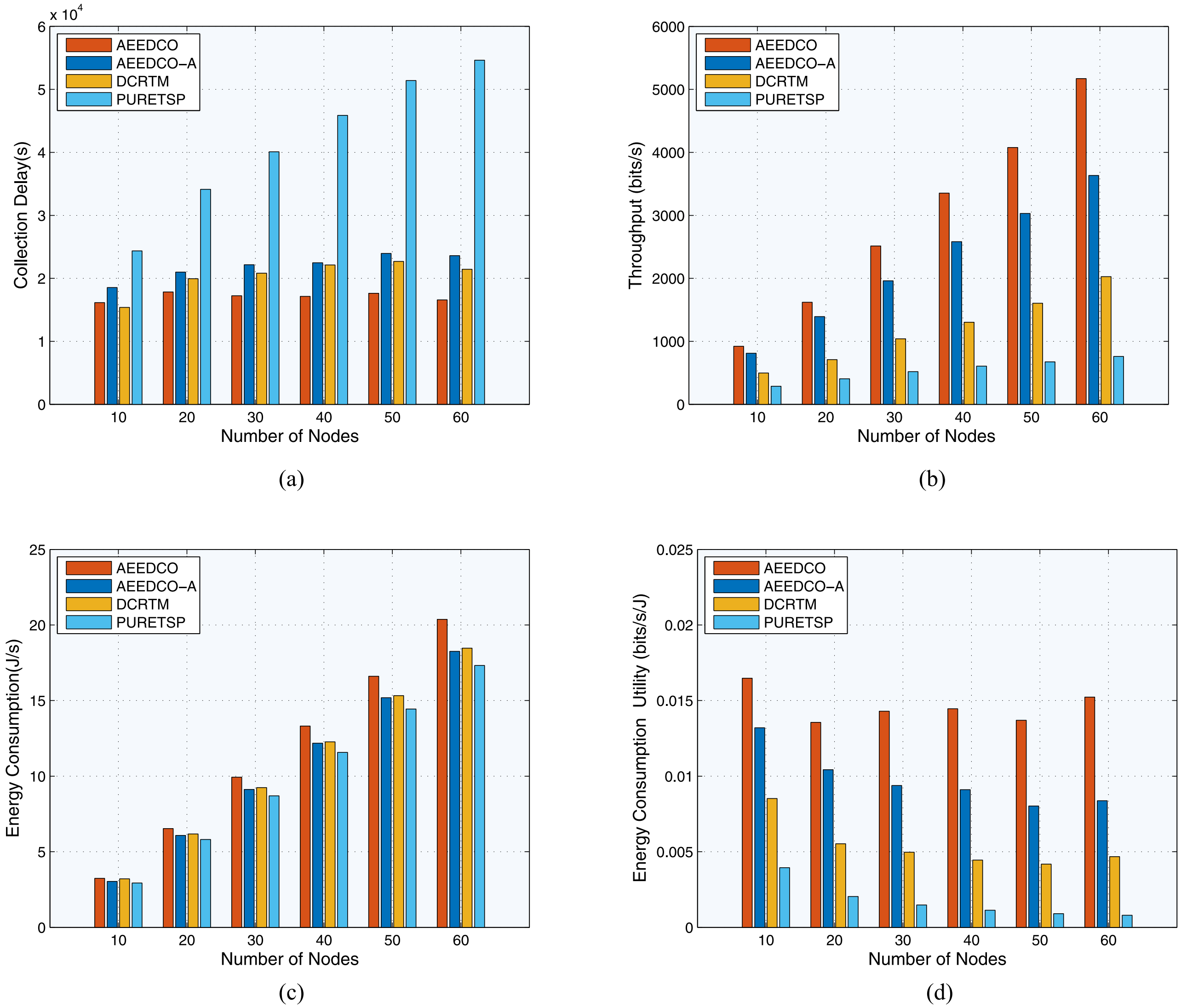

Fig. 4. Simulation results with different numbers of nodes based on S2CR12/24. (a) Collection delay. (b) Network throughput. (c) Energy consumption. (d) Energy consumption utility.

The energy consumption utility defined in (1) is illustrated in Fig. 4(d). The energy consumption utility of AEEDCO, AEEDCO-A, and DCRTM is relatively stable as the number of nodes increases, while that of PURETSP decreases all the way. Among that, the energy consumption utility of AEEDCO is the largest, and that of AEEDCO-A is close to AEEDCO. According to (1), the explanation of energy consumption utility could be based on the network throughput and energy consumption. Because AEEDCO and AEEDCO-A are implemented based on the energy consumption utility and have the mechanism of energy adjustment, the energy consumption utility of them is correspondingly larger than the other two algorithms.

2) Energy Consumption Utility With Different Specifications of Acoustic Modems: As mentioned above, the network performance is closely related to the specification of acoustic modems. Thus, we evaluate the energy consumption utility of these algorithms with different numbers of nodes based on settings of the S2CR12/24 modem and the S2CR18/34 modem, respectively. In this scenario, the velocity of AUV is set as 2 m/s and γ is 8. The result is shown in Fig. 5. Obviously, their performances vary greatly with different specifications of modems, which are equipped with different communication ranges, frequencies, power settings, etc. Hence, the implementation procedure of these algorithms changes greatly. In general, as the number of nodes increases, the energy consumption utility of AEEDCO and AEEDCO-A algorithms has the same tendency in both modem settings. This indicates that both algorithms are relatively robust despite of what the specifications of acoustic modems are.

3) Energy Consumption Utility With Different Velocities of AUV: Since the velocity of AUV affects the performance of the collection delay and the network throughput, which indirectly influence the energy consumption utility. Thus, we evaluate the energy consumption utility with different velocities of AUV based on the setting of the S2CR12/24 modem. In this scenario, the number of nodes is set as 50 and γ is 8. The result is shown in Fig. 6. Apparently, the velocities of

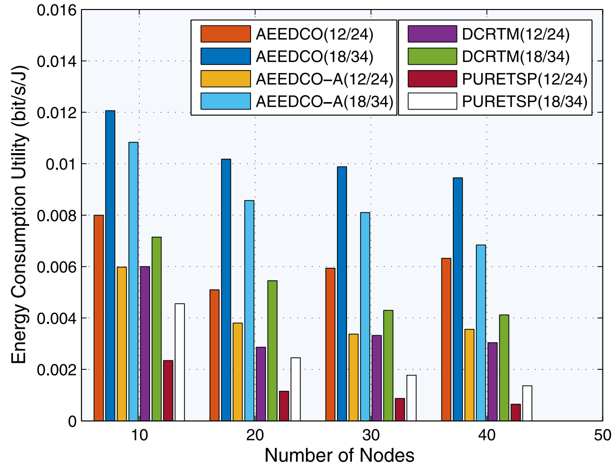

Fig. 5. Energy utility with different numbers of nodes based on S2CR12/24 and S2CR18/34.

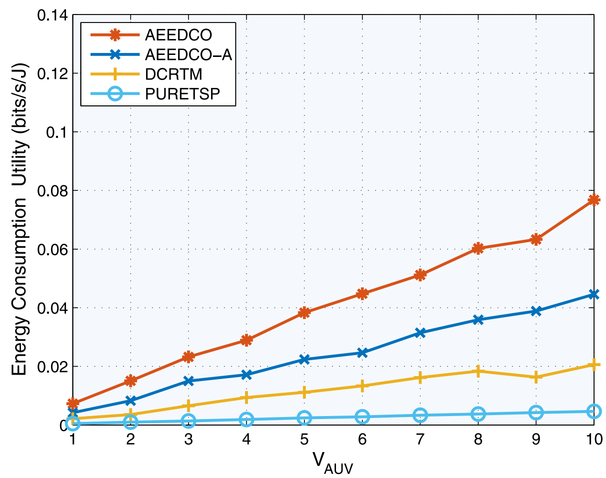

Fig. 6. Energy consumption utility with different velocity of AUV based on S2CR12/24.

AUV affect the performance of AEEDCO, AEEDCO-A, and DCRTM significantly while affecting little that of PURETSP. The reason can be explained as follows. The traveling path of AUV in PURETSP is longer than the others because AUV needs to visit every node in PURETSP while only visit the cluster heads in the other algorithms. Thus, although the velocity of AUV increases, the collection delay and the network throughput of PURETSP could not change a lot and its energy consumption utility correspondingly changes little. In addition, with the increase of AUV velocities, the energy consumption utility of the four algorithms becomes larger. This is because the faster the velocity of AUV is, the shorter collection delay would be and the larger network throughput would be accordingly. As a result, the energy consumption utility becomes larger.

4) Energy Consumption Utility With Different Data Packet Length: Since the data packet length of AUV affects the performance of network throughput and energy consumption, we implement the energy consumption utility with different data packet lengths based on the S2CR12/24 modem. In this case, the number of nodes is set as 50 and the velocity of

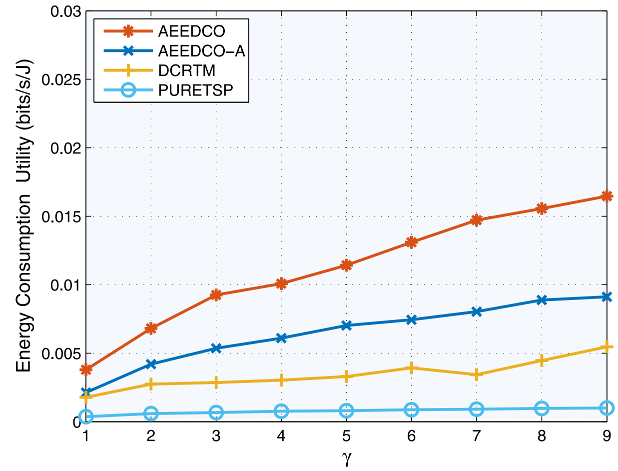

Fig. 7. Energy consumption utility with different data packet length based on S2CR12/24.

TABLE IV
RUNNING TIME OF ALGORITHMS

Number of Nodes	AEEDCO (second)	AEEDCO-A (second)	DCRTM (second)	PURETSP (second)
10	5.449	0.013	0.001	0.107
20	8.829	0.014	0.001	0.588
30	15.167	0.019	0.001	1.866
40	30.158	0.021	0.002	4.355

AUV is set as 2 m/s. As illustrated in Fig. 7, the increase of the data packet length would not bring too much change in the performance of PURETSP while it does influence greatly on that of AEEDCO, AEEDCO-A, and DCRTM. This is because the increase of network throughput of PURETSP is lower than the others, resulting from its long collection delay. In addition, with the increase of the data packet length, the energy consumption utility of the four algorithms becomes larger. The reason can be explained as follows. The performance of the network throughput and energy consumption increases with the data packet length. At the same time, the network throughput increases slightly faster than energy consumption.

5) Algorithm Running Time With Different Numbers of Nodes: Running time is an important indicator of an algorithm. Here, we simply show the comparison of the running time of algorithms under the same simulation environment. Table IV illustrates that the running time of AEEDCO is the longest, while that of AEEDCO-A and DCRTM is no more than 1 s. In addition, the running time of PURETSP is longer than that of AEEDCO-A and DCRTM while shorter than that of AEEDCO. Thus, for a very large network, we should make a careful choice between AEEDCO and AEEDCO-A depending on the network requirements.

VII. CONCLUSION

In this article, we mainly introduced two algorithms, AEEDCO and AEEDCO-A. Aiming to make a tradeoff between the network throughput and the energy consumption, we define a tradeoff factor energy consumption utility and formulate an optimization problem to maximize it. Then, we decompose it into four issues: 1) the selection of cluster heads; 2) the clustering algorithm; 3) the MAC protocol; and 4) the path planning of AUV. Due to the constraint of the communication range, the selection of cluster heads is formulated as an MCP. To reduce the travel time of AUV, the path planning of AUV is formulated as a TSP. Based on these strategies, final clustering results are selected based on maximal energy consumption utility. Results show that the proposed two algorithms perform well and are very promising.

A number of interesting researches are considered to be carried out in the future. To improve the performance of UWSNs, multiple AUVs could also be introduced into the network. The collaboration between multiple AUVs is challenging both in hardware and software. In addition, considering the complicated real sea environment, AUV may not travel with fixed velocities which significantly influences AUV path planning. Besides, the communication between nodes is full of uncertainty depending much on the ocean environment. Hence, the better communication model, network model, and AUV path planning need to be further studied in order to provide a better solution to the AUV-aided data collection network and the IoUT.

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